

# Supporting Interpersonal Communication Using Mind Maps

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**Abstract** Engaging in initial communication interactions with an unknown partner for the first time can be a daunting task. Participants often use several different strategies, including an active strategy involving getting to know their communication partners through asking other people about them. However, this strategy might not always be possible. To resolve the situation when this strategy is not suitable, we propose a method to extract keywords from the partner's comments on SNS sites and use these comments to represent their interests and activities. Keywords are visualized as a mind map for use as a communication tool when engaging in interpersonal communications. The use of this method is demonstrated and evaluated in three examples that were created from real world data collected from Twitter.

**Keywords:** interpersonal communication, mind maps, feature word extraction, Twitter, SNS

## 1. Introduction

Engaging in initial communication interactions with an unknown partner for the first time can be a daunting task. Initial interactions are the entry phase during which participants undergo feelings of uncertainty or unpredictability about their new communication partner<sup>(1)</sup>. People generally use three types of uncertainty reduction strategies (URS's) to get to know a target person: passive, active, and interactive strategies<sup>(2, 3)</sup>.

Passive strategies involve distant observation to get to know the persons and often entail watching their interactions with others. Active strategies call for getting to know the partners without interacting with them, and usually involves consulting others about the partners. In some situations it is not possible to ask a third party about the partners and therefore makes the use of active URS's difficult. Interactive strategies involve directly asking the partners about themselves or informing them about oneself.

The use of mind maps in educational environments has been widely researched with many reporting the benefits of using mind maps in understanding information and learning processes<sup>(4-7)</sup>. Based on this, mind maps could be used to support communication participants in learning about themselves and other participants. This would help to support active URS strategies in getting to know the other participants without con-

fronting them in person. It would also help alleviate three problems that are often faced by interpersonal communication participants: Not knowing what your hobbies and interests are, not knowing what the other participants' hobbies and interests are, and finally, not being able to talk about your own hobbies and interests to other participants effectively. If the communication participants created mind maps about themselves, they can use them as tools to support their expression.

However, it is difficult to draw a mind map as it takes time, effort, and skill. To overcome this problem, in this paper we propose the use of personal information in a subject's Twitter feed, from which feature words are extracted automatically to generate a mind map.

A mind map is drawn by starting in the center with the keyword or image that is central to the concept. From this center, keywords or images expand in a radial pattern, linked back to the central concept through contextual relations<sup>(8, 9)</sup>. Drawing mind maps can be seen as taking related words one-by-one and searching for more related words, and then reiterating.

## 2. Related Work

### 2.1 Mind maps in education

There has been a lot of research into the use of mind maps in educational environments. Hwang et al.<sup>(4)</sup> used a grid-based knowledge acquisition approach and generated Mindtools to help students organize and share knowledge in field assignments. In an experiment, elementary school students used it to identify species of

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butterflies and it was found to improve the students’ learning, and also their ability to identify species in the field.

Zouaq and Nkambou<sup>(10)</sup>, examined automatically generated domain models from text documents for use in e-learning. Domain ontologies of the text were built and then used to construct domain models. The results were superior when compared to previous software. Perez-Marin et al.<sup>(7)</sup> proposed the use of concept maps to automatically generate students’ conceptual models from plain text answers. These conceptual models can provide teachers with an insight into the students’ conceptual understanding of the material being taught. Lau et al.<sup>(11)</sup>, used concept maps automatically generated from e-learning environment messages to help teachers quickly understand their students learning progress and provide appropriate guided responses. Kusama et al.<sup>(5)</sup>, proposed using a hybrid method of PC based note-taking and mind maps to support hearing-impaired students during classroom lectures. The addition of using mind maps to summarize the content of the lectures proved effective in providing assistance and facilitating student comprehension in university settings.

We thought that using mind maps for summarization of a learner’s comments on SNS sites could help individuals better understand both their interests and activities and those of others.

## 2.2 Mind maps in communication

There is also research on the facilitation of communication by using mind maps. Nuutinen et al.<sup>(6)</sup>, used social mindtools to enhance user understanding of the structure of the documents being composed in a collaborative learning environment. They found that novice users better understood the overall structure of the document, which enabled them to contribute more effectively when compared with other text-oriented Web 2.0 tools, such as wikis. Takaishi and Nagae<sup>(12)</sup> examined the effectiveness of mind maps in improving the communication skills of nursing students. Using more than 20 years of historical data, they drew a mind map of the processes of working with patients of schizophrenia. Then they analyzed the mind map use to determine the changes in the understanding and communication. The use of mind maps was seen effective in helping the nursing students visualize understanding of their own information, and considering more effective patient

care.

In this paper, we propose that by presenting participants with mind maps of their interests and activities, they can find the common interests and communicate effectively.

## 3. Automatically Generated Mind Maps

### 3.1 Searching for related words one-by-one

Drawing a mind map can be thought of as a problem of searching one-by-one for related keywords, starting in the center with the keyword or image that is central to the concept. The related keywords or images are reiterated and expand in a radial pattern, linking back to the central concept through contextual relations. In this paper, the frequency of co-occurrence between words is used as a measure of the degree of the relation. Figure 1 is the formula used to determine the frequency of co-occurrence  $Rel(a, b)$ , where  $a$  is the parent node word, and  $b$  is the child node word, and  $D(w)$  is the number of sentences that contain the word  $w$ .

A threshold is used to determine what degree of the frequency of co-occurrence warrants a parent and a child nodes being linked. Figure 2 demonstrates how links between parent and child nodes are determined. The frequency of co-occurrence between parent node  $a$  and each of the child nodes is calculated, and it is deter-

$$Rel(a, b) = \frac{|D(a) \cap D(b)|}{|D(b)|}$$

Figure 1. Frequency of Co-occurrence Formula.

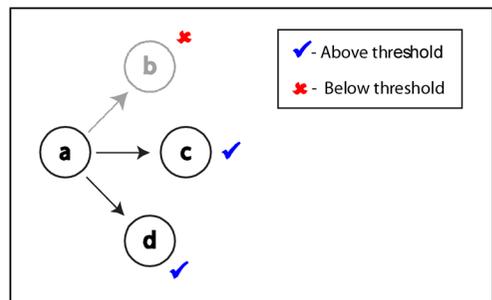


Figure 2. Graph of Determining Node Links Using the Frequency of Co-occurrence Threshold.

```

input : w;
nextnodes = {w};
while (nextnodes is not empty)
{
  n = get_first_node(nextnodes);
  child = get_child(n);
  foreach c (child)
  {
    addedge(n, c);
    addnode(nextnode, c) if not appeared(c);
  }
  deletenode(nextnode, n)
}
    
```

Figure 3. Digraph Expansion Algorithm.

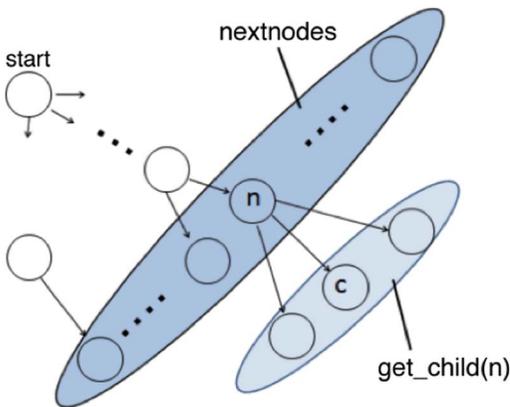


Figure 4. A Graph for Writing a Nextnode.

mined that child node *b* is below the threshold and therefore not linked to parent node *a*. Child nodes *c* and *d* are above the threshold and therefore linked as a relation to parent node *a*.

### 3.2 Automatic Mind Map Generation

An algorithm is used to create a mind map represented as a digraph, as shown in the pseudo code in Figure 3. It starts with a word *w* that is used to find nextnodes to which nodes are linked one-by-one by a direction edge. Figure 4 shows how nextnodes are added to the graph in the expansion process.

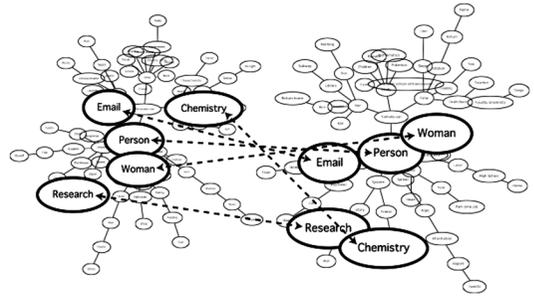


Figure 5. Maps of Subject B (Right) & Subject C (Left).

## 4. Mind Maps Generated from Sample Data

### 4.1 Data collection

We decided that the history of personal Tweets on Twitter would be used as sample data. Using the Twitter API, we collected the history of three subjects' personal Tweets; subjects A, B and C had 1182, 1508, and 3200 Tweets, respectively.

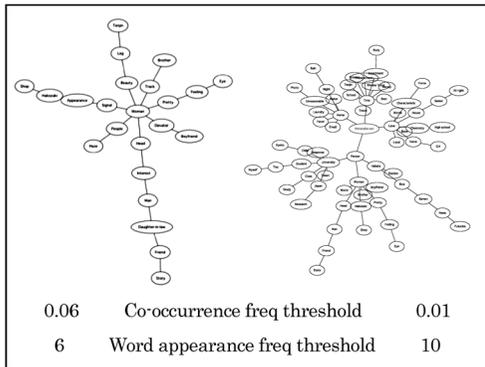
### 4.2 Data analysis and mind map generation

The sample data were indexed using the GETA (Generic Engine for Transposable Association) search engine to extract feature words from sentences. These feature words were then processed using the frequency of co-occurrence and digraph expansion algorithm that were introduced in the previous section. The output of the algorithm was then used to draw the resulting mind map using GraphViz.

### 4.3 Examples of generated mind maps

Examples of mind maps were created using the sample data from the three subjects. Figure 5 shows the two mind maps that were generated using subjects B's and C's sample data with the same co-occurrence frequency threshold and word appearance frequency threshold of greater than 0.01 and 1.5 respectively.

There are four nodes connected to the central node of subject B's mind map: "home", "time", "love", and "person". Then three feature words are connected to the "love" node: "chemistry", "words", and "house" which



**Figure 6.** Effect of Thresholds on Mind Map Structure.

were likely to have been used together within a single Tweet along with the parent node. Once again, looking at the central node, the connected nodes are “person” – “university” – “professor” – “study” which we can imagine have been used in the following way: “The professor called to say come to the university and study”. By looking at not just a single unit but also the relation between words and the way they are connected, the subject’s interests and activities can be discovered.

To use mind maps for supporting interpersonal communication, the users start by looking at each other’s mind maps trying to find common keyword nodes that represent the interests and activities and can be used as topics for discussion. An example of this can be seen in the sample mind maps of subjects B and C’s. They share five similar nodes that can be common topics for discussion: “chemistry”, “email”, “person”, “woman”, and “research”. Users can also find out more about their communication partner by examining the surrounding nodes that are connected to the common keyword nodes. Looking at subjects B and C’s maps we can find subtle differences in the common nodes, such as the nodes connected to the “chemistry” node. Subject B’s node is connected to the nodes “story” and “research”, whereas subject C’s is connected to the nodes “high school” and “love”.

## 5. Evaluation

### 5.1 Evaluation of mind map interface

By varying two thresholds, the frequency of the co-

occurrence threshold and the frequency of the word appearance threshold the size and complexity of generated mind maps can be controlled as shown in Figure 6 by using the same subjects’ sample data from Figure 5. The mind map on the left is sparse when compared to the map on the right, which has a dense and complex structure. An evaluation of the structure and complexity of the generated mind maps was performed as they can play an important role in the readability and use of the maps.

Nine university students, including the three subjects A, B and C, participated in the evaluation of six different mind maps. They were asked to judge subjectively from the viewpoint of “ease of reading” as a mind map. The six mind maps were divided into three groups based on the total number of nodes: less than 30 nodes, 30 to 70 nodes, and 70 to 100 nodes. In each group one map had a high co-occurrence frequency threshold and therefore few branches, and the other map had a low co-occurrence frequency threshold, which resulted in many branches. The student evaluators were asked to select from each group the map that had a greater ease of reading. The results for maps with less than 70 nodes indicated that maps with many branches were easier to read than those with few. For maps with greater than 70 nodes there was a slight preference towards maps with fewer branches.

The student evaluators were then asked to select, based on the number of nodes in the three groups, which mind maps were easy to read. The results showed a clear preference for mind maps with less than 70 nodes in regards to ease of reading.

### 5.2 Map contents

A five-step scale questionnaire was used to evaluate how the mind maps that were created from the sample data represent the interests and activities of the subjects. The subject whose data were used to create the mind map as well as the partners of the subject answered the questionnaire. Subjects A, B, and C evaluated each other’s mind maps using the questionnaire. Subjects were asked to rate on a five-step scale how well they thought the mind map they selected in section 5.1 represented their interests and hobbies. Then they were shown the maps of their partners and asked to rate the relevance on the same scale. The results of the evaluation are summarized in Table 1. From these results,

**Table 1.** The Evaluation Results with the Content.

	Subject A			Subject B			Subject C			Average
Actual person	4			4			3			3.67
Partner	4	5	4	4	4	5	5	5	5	4.56

Partner Actual Person	A	B	C
A		<b>Feature words X1:</b> Study, Exam, Research, Work, Man, Information, Friend, Yen 4	<b>Feature words X2:</b> Friend, Photo, Woman, Email, Ito, Research, Study, Professor 4
B	<b>Feature words X1:</b> Study, Exam, Research, Work, Man, Information, Friend, Yen 5		<b>Feature words X3:</b> Chemistry, Study, Tweet, Boyfriend, Woman, Friend, Talk 3
C	<b>Feature words X2:</b> Friend, Photo, Woman, Email, Ito, Research, Study, Professor 1	<b>Feature words X3:</b> Chemistry, Study, Tweet, Boyfriend, Woman, Friend, Talk 2	

**Figure 7.** Evaluation of Whether Common Topics can be Used for Communication.

the subjects all agreed that the mind maps represented their interests and activities.

Subjects were then asked to rate on a five-step scale how confident they were that a normal conversation could be held on the common topics displayed within their own mind map and the partner’s mind map. The results of the evaluation are displayed in Figure 7 with two thirds evaluating that they thought a normal conversation could be held on the common topics that were displayed in the mind maps.

## 6. Conclusion

In this paper, we proposed the use of automatically generated mind maps to help support interpersonal communication partners when participating in a conversation or discussion with non-acquaintance partners. Using the Twitter API, we collected the Tweet histories of three subjects; the Tweets contained personal information and were used as sample data. Characteristic keywords were then extracted from the sample data and

used to automatically generate mind maps by using the frequency of co-occurrence and a digraph expansion algorithm. These mind maps were then evaluated by each of the three subjects on the appropriateness of the contents. It was determined that common keywords could be found and that the mind maps created using the SNS data were good representations of the subject. The subjects also evaluated whether they thought they could hold a normal conversation on the common topics and we found that two thirds had a degree of confidence on this point.

The interface of automatically generated mind maps was also evaluated by nine university students, including the three subjects, in regards to the “ease of reading”. We found that mind maps with less than 70 nodes and many branches were given a higher ease of reading.

In the future, we plan to investigate the use of mind maps in searching for language exchange partners that have similar common interests.

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